Uncovering relationships between environmental metrics in the multi-objective optimization of energy systems: A case study of a thermal solar Rankine reverse osmosis desalination plant

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Abstract

Multi-objective optimization (MOO) is increasingly being used in a wide variety of applications to identify alternatives that balance several criteria. The energy sector is not an exception to this trend. Unfortunately, the complexity of MOO grows with the number of environmental objectives. This limitation is critical in energy systems, in which several environmental criteria are typically used to assess the merits of a given technology. In this paper, we investigate the use of a rigorous dimensionality reduction method for reducing the complexity of MOO as applied to an energy system (i.e., a solar Rankine cycle coupled with reverse osmosis and thermal storage). Instead of using an aggregated environmental metric, a common approach for reducing the number of environmental objectives in MOO, we propose to optimize the system in a reduced search space of objectives that fully describe its performance and which results from eliminating redundant criteria from the analysis. Numerical results show that it is possible to reduce the problem complexity by omitting redundant environmental indicators from the optimization.

Keywords: decision-making, multi-objective optimization, life cycle assessment (LCA), solar energy, modelling, delta error, mixed-integer non linear programming (MINLP)

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1. Introduction

Multi-criteria optimization arose from the economic equilibrium and welfare theories, game theory, and pure mathematics [1]. Nowadays it is an essential tool in many fields like economics, logistics, management and engineering. When designing any technological process, it is desirable to find the best possible alternatives, which implies dealing with several criteria simultaneously [2]. Multi-objective optimization (MOO) has recently gained wider interest in energy applications following the trend of the modern society towards more sustainable process that balance economic, social and environmental criteria.

In 2011, 119 countries committed for renewables' support, the majority of which are developing. According to EU regulations, 22 % of total electricity production should be provided by renewable sources. As a result, in last years renewable energies significantly advanced, offering a row of environmental benefits to the society [3], [4], [5], [6]. The adoption of renewable energy sources raises some concerns related with energy efficiency, cost, and environmental benefits. In this context, the application of MOO techniques holds good promise [7], [8],[9], [10], [11]. Alarcon et al. in their review paper examine the existing multi-objective planning strategies for the optimal integration of Distributed Energy Resources to minimize the operation cost, reduction of carbon emissions and network energy losses [12]. Alonso et al. applied MOO to the reactive power planning (management) considering voltage stability, power losses, and cost of reactive power sources shifting [13]. Moura et al. addressed the intermittency of the renewables using a MOO model that optimizes the mix of the renewable system considering its contribution to the peak load and the combined intermittence and total cost [14]. Other works have focused on incorporating environmental aspects in energy systems. In this regard, life cycle assessment (LCA) [15] has emerged as an effective methodology to assess the environmental performance of products and processes. LCA is used to quantify the environmental loads associated with any process over its entire life cycle in terms of

several impact categories such as climate change, land use, ozone depletion etc. The main advantage of LCA is that it accounts for the environmental burdens of a technology over its entire life cycle, which avoids shifting these burdens from one part of the energy supply chain to another. Livingston and Pistikopoulous [16, 17]and later, Azapagic and Clift [18] were the first to couple LCA with MOO. This general framework has been applied to a wide variety of problems, including some applications in the energy sector. Bernier et al. studied the integration of a CO_2-capture process using monoethanolamine in a natural gas-combined cycle power plant. They simultaneously optimized the column dimensions, heat exchange, and absorbent flow configuration considering two objectives: the levelized cost of electricity and its life cycle global-warming potential [19]. Alexander et al. apply LCA to minimize the acidification potential and direct contribution to greenhouse gases of a nitric acid plant along with the internal rate of return [20]. Some other applications of LCA and MOO can be found elsewhere: design of absorption cycles [21, 22], production of chemicals and in particular of hydrogen cyanide [23],design and planning of a district heating network based on centralized and decentralized heat pumps combined with on-side cogeneration [10],and supply chain problems [24–26]. Unfortunately, the computational burden of MOO increases with the number of objectives. One possible manner to overcome this limitation consists of using aggregated LCA indicators, which are defined from a set of impacts using normalization and weighting parameters. This approach is inadequate as it may change the structure of the underlying MOO problem, in a manner such that some solutions might be left out of the analysis [27]. An alternative approach to decrease the number of objectives is to use dimensionality reduction methods. These techniques identify redundant criteria that can be omitted from the problem while still preserving its structure to the extent possible. In a pioneering work, Deb and Saxena [28] proposed a method based on principal component analysis (PCA) to identify redundant objectives in MOO. This method does not include any quantitative indicator

to measure how much the initial structure of the problem is changed compared to the initial one. Later, Brockhoff and Zitzler proposed two algorithms to identify a minimum meaningful objective subset out of an initial set of objectives. This analysis aims to rule out the redundant criteria and keep only the functions that preserve the dominance structure of the primary set. The deviation of this minimum objective subset from the initial one is measured using a metric (i.e., delta-error) [29].More recently, Thoai proposed some ways to reduce the number of criteria and the dimension of a linear multiple criteria optimization problem using the concept of so-called representative and extreme criteria [30], while López et al., introduced two new algorithms to reduce the number of objectives in multiobjective optimization based on a feature selection technique [31]. This work addresses the problem of dimensionality reduction in MOO models in the context of energy systems (i.e., design of desalination plants coupled with a solar Rankine cycle and thermal energy storage, TES). The main goal of this piece of research is to show how the use of dimensionality reduction techniques enables the identification of redundant environmental criteria in the multi-objective optimization of energy systems, shedding light on their environmental performance in several damage categories. The article is structured as follows. The problem of interest is formally stated in Section 2. Section 3 describes the mathematical MINLP formulation derived to tackle this problem, while in section 4 the solution procedure is outlined. Some numerical results are presented in Section 5, finally the conclusions of the work are given in Section 6.

2. Process description

As a benchmark problem to illustrate the advantages of using dimensionality reduction in energy problems, we consider the design of a reverse osmosis desalination plant coupled with solar Rankine cycle and thermal energy storage. Most of the studies performed on the optimization of similar systems were limited in scope as the economic

performance was often chosen as the single criterion to be optimized. Vince et al. addressed the simultaneous optimization of the economic performance and environmental performance of a desalination plant operated with fossil fuel [32]. Spyrou and Anagnostopoulus studied a desalination facility coupled with a renewable source of energy and a storage unit seeking for the system design satisfying minimum cost and maximum water needs fulfilment [33]. Salcedo et al. optimized a desalination plant coupled with solar collectors and thermal energy storage [34] in order to find an optimum design of the system simultaneously satisfying minimum production cost and environmental impact.

The scheme of the process considered in our study is shown in Fig. 1. A detailed description of the system can be found in [34]. For the sake of completeness of this work, we provide next a brief description of such a facility. Reverse osmosis produces potable water from saline one using a membrane operating under high pressure. The process requires a standard RO unit with several trains, each one operated by one high pressure pump P_{RO}. In every train pressure vessels are arranged in arrays (2:1 or 4:2) and connected in parallel. From 1 to 8 spiral-wound membranes can be allocated in series inside a pressure vessel. After passing through membranes, the still pressurized brine is routed to a hydroturbine (H) to recover part of the energy required for the RO operation. A Rankine cycle is used to provide the electricity needed for operating the RO high pressure pump. In the boiler, the water, which is the working fluid in the cycle, exchanges the thermal energy with oil, circulating in the solar-thermal system. The superheated steam formed in this way is expanded further in the turbine (T), thereby producing electrical energy. A small part of this energy is used to operate the RC pump. After the turbine, the humid vapour fully condensates in the condenser and then comes back to the boiler. A solar thermal unit is coupled with the cycle in order to generate heat for its boiler. Mineral oil is used as a working liquid in the solar system. The oil passes through the parabolic through collectors where it absorbs the solar energy. A thermal energy storage is incor-

porated in the system in order to save the surplus energy generated in those periods with a high solar radiation in which the solar energy exceeds the demand. When the energy cannot be delivered from the collectors due to weather intermittencies, and neither from the heat storage, the system operates the gas fired heater in order to maintain the oil temperature constant, thereby ensuring a safe running of the RC. Given are a target water demand to be fulfilled, climatic and economical data, characteristic of the membranes, collectors and heat storage system, environmental impacts associated with utilities and construction materials. The goal is to find the optimal process design simultaneously minimizing unitary production cost and unitary environmental impact.

3. Mathematical model

To model the design task, we used as a baseline the MINLP formulation introduced in [34], where the economic performance was assessed by the unitary production cost while the environmental impact was quantified according to the unitary environmental load. In the original bi-criteria MINLP, the environmental impact was evaluated via the LCA method CML 2001. In this study, we employ instead the Eco-indicator 99, which accounts for several individual impacts aggregated in three damage categories. The impact assessment method Eco-99 indicator is a damage oriented approach whose value is determined from the life cycle inventory of inputs and outputs (LCI) of a process, a set of damage factors, and several normalization and weighting parameters. Details on this metric can be found elsewhere [35, 36]. We consider 11 environmental objectives: 10 individual impact categories, and one aggregated metric:

- Ecosystem quality: toxic emissions, acidifcation and eutrophication, land occupation and land conversion
- Human health: carcinogenic effects, respiratory effects, climatic change, ozone layer depletion, and ionizing radiation.

- Resources: extraction of minerals, extraction of fossil fuels.

The design task is finally expressed as a MOO problem with 12 objectives and is hard to solve due to the large number of objectives included.

Following the work by Kostin et al. [37], we consider the following general multi-objective minimization problem $M(X)$:

$$\begin{aligned} M(X) = &\min_{X}(F(x) = \{f_1(x), f_2(x), \ldots, f_k(x), \ldots, f_O(x) : x \in X\}) \\ \text{subject to } & g_n(x) \leq 0, \quad n = 1, 2 \ldots, N \\ & h_{n'}(x) = 0, \quad n' = 1, 2 \ldots, N' \end{aligned} \tag{1}$$

where O objective functions are optimized, N is the number of inequality constraints, and N' is the number of equality constraints. x is a vector of decision variables, X is the search space, while $F(x)$ denotes the vector of objective functions $f_k(x)$. The set of values of the objective functions $f_k(x)$ corresponding to the feasible solutions of MO constitute the feasible objective space Z. In the context of our problem, one of the objectives f_k represents the economic performance, whereas the others quantify a set of environmental impacts.

4. Solution method

Several MOO solution methods can be used to produce the Pareto solutions of the model. These methods, however, are very sensitive to the number of criteria considered in the analysis. We propose here to use the ε-constraint method to generate a set of Pareto solutions, and then apply a rigorous MILP-based dimensionality reduction method to identify redundant objectives and key environmental metrics. Following this strategy, we first optimize each objective function separately seeking for the extreme solutions of each objective. The economic function is then retained in the objective function while the

environmental objectives are transferred to auxiliary constraints that impose bounds on them. By systematic narrowing these bounds, we can produce a set of Pareto solutions [38]. Each of these Pareto solutions represents a design alternative with a different environmental and economic performance. After generating these first set of solutions, we apply an objective reduction technique that identifies redundant functions, thereby reducing the dimension of the original data set while still preserving its main features with accuracy. After discarding the redundant criteria, the MOO solution procedure can be applied again in a reduce domain of objectives, which reduces its computational burden.

The objective reduction method is used to substitute the original set of objectives by a qualitatively similar contracted set of criteria. This qualitative similarity can be measured by an error of ruling out the remaining objectives (referred to as δ-error). The concept of δ-error was first introduced in [29]. The core idea of this approach is to measure the difference in the dominance structure between the original set and a reduced one. We consider the weekly Pareto optimal concept: solution A is said to be weekly dominated if there is not any solution better than it in all the objectives simultaneously. An illustrative example is provided in Fig. 2(a) , where 3 Pareto solutions and 3 objectives are considered. Fig. 2 is a parallel coordinate plot [39, 40]. This type of plot, in a nutshell, enables to visualize multivariate data (i.e., Pareto solutions with several objectives), using a 2D pattern. The three plotted solutions s_1 (solid line), s_2 (dotted line) and s_3 (dash-dotted line) are weakly Pareto-optimal. In the parallel coordinate plot, the x-axis represents the set of objectives, while the y-axis corresponds to the normalized values of the objectives attained by each solution. Every polyline (with its vertices placed in a given objective) in the parallel coordinates plot represents a single solution. In Fig. 2(a) we show the original set of functions and reduced sets resulting from removing every single objective 2(b-d). There are 3 cases: when we remove $f_1(x)$ (b), $f_2(x)$ (c) or $f_3(x)$ (d). When all objective functions are present (a), there is no solution which would dominate others ((i.e., would be better

simultaneously in all three objectives). The analysis of the solutions reveals that s_3 is the best in objective $f_1(x)$, s_2 in $f_2(x)$, and s_1 in $f_3(x)$ (assuming that we aim to minimize all the objectives simultaneously). Ruling out one of the objectives from the original set may change the dominance structure of the problem. When we consider the reduced set without f_2 (c) the dominance structure will be preserved: there is no one solution dominating other solutions in all objectives. Thus, the reduced set of objectives F'=$f_1(x)$,$f_3(x)$ is non-conflicting with the original set F=($f_1(x)$,$f_2(x)$,$f_3(x)$). However, by excluding $f_1(x)$ (b) or $f_3(x)$ (d) we change the dominance structure of the initial set. Thus, in case (b) s_3 is dominated by s_2 and s_1 in objectives $f_2(x)$ and $f_3(x)$, while in case (d) s_1 is dominated by s_2 in objectives $f_1(x)$ and $f_2(x)$, therefore s_3 and s_1 can be discarded respectively from the sets (b) and (d) as they become sub-optimal or redundant in the reduced set of the objectives. The error of omitting one of these redundant objectives is referred to as delta error [23, 20]. The difference between the true value of objective 1 in solution 2 and 3 ($\delta 1$), and in objective 3 in solution 2 and solution 1 ($\delta 2$), in the original space of objectives can be used as a measure to quantify the change in the dominance structure. Note that, if we rule out the second objective as it shown in the Fig. 2(c), the dominance structure will be preserved. The goal of our analysis is then to identify sets of objectives that lead to low approximation errors.

A rigorous MILP formulation was presented in [41] to accomplish this task. For the sake of simplicity, technical details on this MILP are omitted, as the interest here is on exploring the advantages of this approach as applied to the design of a complex facility where energy generation plays a major role. For further details one can address our previous study [42]. Applications of dimensionality reduction methods to other MOO models can be found elsewhere [37, 43, 44].

5. Numerical results

The purpose of this study is to get explicit insight into the environmental performance of a desalination plant coupled with a renewable energy system. The matter of interest is to analyse the results obtained by using different environmental metrics and to establish whether the aggregated metric provides the same information as the individual impact categories. With this idea in mind, we optimized 12 objectives: unitary production cost of potable water, and 11 environmental impact categories. A set of Pareto points was generated by solving 11 bi-criteria problems (unitary production cost versus each single environmental impact category). The model was implemented in GAMS and solved using CONOPT on a Athlon(tm) II X2 B24, processor 2.99GHz, 3.49 GB of RAM (see [34] for details on solution procedure). In this case study we consider a desalination plant assuming weather data in Tarragona. It consists of 4 units: reverse osmosis, Rankine cycle, solar-thermal unit and energy storage. The filtration of the water takes place in the reverse osmosis unit using a high pressure pump, while the Rankine cycle supplies electricity to operate this high pressure pump. The steam required by the Rankine cycle is generated with a solar-thermal unit. The solar collectors operate during sunny days, while a gas fired heater and a storage device provide thermal energy for steam generation in periods when direct solar thermal energy coming from the collectors is not sufficient. The environmental impact of the process takes into account the damage caused during the plant operation (electricity and natural gas used in the gas fired heater) and that associated with the construction phase. Further details on the LCA calculations can be found elsewhere [34]. Following the procedure described above, we generated 473 solutions that were normalized by dividing the objective values by the maximum one attained over all the solutions. Fig. 3 shows these points in a parallel coordinates plot, where the normalized values are displayed for every objective. This figure provides insight into the Pareto structure of the problem. Particularly, a preliminary inspection of the curve

reveals that there are some clear conflicts between objectives. For instance, STC seems conflicting with Eco-99, land occupation and carcinogenic effects. Similarly, carcinogenic effects are conflicting with climatic change, climatic change with ionizing radiation, ionizing radiation with ozone layer depletion, and finally fuel depletion with minerals. In contrast, Eco-99 seems non-conflicting with acidification and eutrophication, ozone layer depletion, respiratory effects and fuels depletion. As will be explained later in the article, these conflicts arise when the same factor has opposite contributions to different environmental metrics.

In Fig. 4, all the solutions of the bi-criteria optimizations are depicted in a 2-D plot that provides the normalized values of the total cost and the environmental performances. That is, we should, for each solution (i.e., operating conditions and design features), the normalized values attained in every environmental damage category. We distinguish two clusters of LCA metrics according to their behaviour. The first cluster includes the following indicators: carcinogenic effects, minerals extraction, ionizing radiation, and toxic emissions. As seen, the curve associated with these points is opened rightwards (there is a lower branch that is monotonically increasing and after reaching a minimum value of the STC it changes the direction continuing with a monotonic raise in terms of LCA metric, while the STC starts increasing). The second cluster of LCA metrics leads to curves that are monotonically decreasing.In this group, we find fuel extraction, ozone layer depletion, acidification and eutrophication, climatic change, land use and occupation, respiratory effects, and total Eco-99.

Fig. 5 shows the projections of the solutions obtained from the bi-criteria optimizations onto the (total Eco-99, STC) space. As observed, using the total Eco-99 as unique environmental metrics is inadequate, since we lose those Pareto solutions that lie above the Pareto set (Eco-99,STC). In other words, some solutions that are Pareto optimal in the original space, cannot be identified in the reduced space Eco-99 vs STC, as they become

suboptimal in such reduced domain. It is thus clear that using a single aggregated metric has the risk of ruling out optimal solutions. Not that, a minimum point is encountered in the curves of those metrics belonging to the first cluster (carcinogenic effects, minerals extraction,ionizing radiation, and toxic emissions) mainly because the impact of the construction becomes important at some point, while it does not affect in the same manner the metrics of the second cluster (fuel extraction, ozone layer depletion, acidification and eutrophication, climatic change,land use and occupation, respiratory effects, and total Eco-99). Further inspection of these results show that the impact reduction is achieved by placing more solar collectors and also by increasing the TES capacity. This is achieved at the expense of increasing the STC. Thus, the minimum SEI design contains the largest collectors area, storage capacity, and consequently the highest STC.

The effect of using a certain LCA metric can be further analyzed by examining the main sources of impact.

Figures 6 and 7 show a breakdown of the impact for the extreme solutions. In our case, the two main sources of impact are operation (mainly natural gas) and construction. The impact of construction becomes prevailing in LCA metrics belonging to cluster 1.

In the min STC solution (Fig. 6), the operation impacts are prevailing in all objectives, whereas in the minimum SEI (Fig. 7) solution in carcinogenic effects, minerals, radiation, toxicity, - the construction becomes dominant. By further analysing the structure of the impact we find out that 90 % of the impact is attributed to the TES, specifically to molten salts. Hence, molten salts lead to more carcinogenic effects, increased extraction of minerals, higher radiation and toxicity but do not affect to the same extent the categories extraction of fossil fuels, ozone layer depletion, acidification and eutrophication, climatic change, land occupation and conversion, respiratory effects and total Eco-99.

We next applied our MILP for dimensionality reduction to get further insight into the problem. Details on this method can be found elsewhere [24]. The goal was to identify

minimum subsets of objectives that preserved the problem structure to the maximum extent possible. We used this MILP iteratively, that is, determining the approximation error for all combinations of 2 and 3 objectives, while retaining always the cost in the reduced model. The results are given in Tables 1 and 2. The minimum delta value (i.e., 36.3) for the bi-dimensional case corresponds to the pair STC and toxic emissions. This indicates that two objectives are not enough to approximate the problem with accuracy. Adding an additional objective to the pool provides much better results. Particularly, STC (1) and extraction of minerals (12) along with any of the following LCA metrics: total Eco-99 (2), land occupation and conversion (5) or climatic change (7), yield a delta value of 0.17. The same objectives (1 and 12) combined with respiratory effects (9) and extraction of fossil fuels (10) lead to a delta equal to 0.1. These results show that objectives 2, 5, 7, 9 and 10 are redundant and at the same time conflicting with objective 12. Going deeper into the analysis we find that the combination of 1 and toxic emissions (4) with any of the following objectives: 2, 3, 5, 7, 9, 10, 11; and combination of 1 and carcinogenic effects (6) with any of the following impacts: 2,3,5,7,9,10,11; combination of 1 and ionizing radiation (8) with any of 2,3,5,7,9,10,11 also results in a small value of delta, and allows us identifying 2 clusters of functions : first - 2, 3, 5, 7, 9, 10, 11; and second 4, 6, 8, 12 (see the list of the objectives in Table 3).

Two main conclusions can be drawn from these analysis: 1) those objectives whose combinations within a single group lead to large approximation errors form a cluster that contains redundant information; 2) objectives belonging to different clusters are conflicting with respect to each other (i.e., interconflicting) 3) to preserve the original structure (to have the minimum delta error) of the problem in the reduced set of objectives we need to keep at least one objective from every cluster. The application of the MILP for dimensionality reduction produces results that are consistent with the graphical analysis discussed before. The advantage of this MILP is that it identifies redundant objectives

in a systematic manner, and enable us to focus on a reduced number of environmental indicators.

6. Conclusions

In this work we have studied the application of a rigorous dimensionality reduction method in the multi-objective optimization of a complex facility in which the use of a renewable energy source plays a major role. We have shown that the use of bi-criteria optimization models where the environmental performance is quantified using a single aggregated LCA metric is not a good practice, as this does not provide complete information on the behaviour of the individual categories (which can be sometimes conflicting). Our systematic MILP allow us to identify redundant environmental indicators that can be omitted while still preserving the problem structure to the extent possible. This simplifies the optimization task and the analysis of the solutions, and makes it possible to focus our attention on a reduced number of meaningful damages that quantify the environmental performance with accuracy.

Acknowledgements

The authors would like to acknowledge financial support from the Spanish Government CTQ2009-14420-C02-01, ENE2011-28269-C03-03, ENE2011-22722) and to thank the Catalan Government for the quality accreditation given to their research groups SUSCAPE and GREA (2009 SGR 545, 2009 SGR 534).

7. Nomenclature

Abbreviations

$Eco-99$	Total environmental impact of the process over its whole life cycle
$EIacid$	Environmental impact related to acidification and eutrophication
$EIcarc$	Environmental impact related to carcinogenic effects
$EIcli$	Environmental impact related to climatic change
$EIfuel$	Environmental impact related to extraction of fossil fuels
$EIland$	Environmental impact related to land occupation and land conversion
$EImin$	Environmental impact related to extraction of minerals
$EIrad$	Environmental impact related to ionizing radiation
$EIresp$	Environmental impact related to respiratory effects
$EIozon$	Environmental impact related to ozone layer depletion
$EItox$	Environmental impact related to toxic emissions
LCA	Life cycle analysis
LCI	Life cycle inventory
$MILP$	Mixed integer linear problem
$MINLP$	Mixed integer non-linear problem
P_{RO}	Pump of Rankine cycle
RO	Reverse osmosis
RC	Rankine cycle
STC	Specific total cost
SEI	Specific environmental impact
TES	Thermal energy storage
X	Search space
Z	Feasible objective space

Sets/indices

F Set of objective functions indexed by f

F' Reduced set of objective functions

Parameters

N Number of inequality constraints

N' Number of equality constraints

O Number of objective functions which were optimized

s Solution

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List of Tables

Table 1: **Delta error for combination of 2 objectives**

Reduced set		Delta
1	2	48.67
1	3	48.67
1	4	36.3
1	5	48.67
1	6	55.29
1	7	48.67
1	8	55.29
1	9	48.67
1	10	48.67
1	11	48.67
1	12	55.29

Table 2: **Delta error for combination of 3 objectives**

Reduced set	Delta	Reduced set	Delta	Reduced set	Delta	Reduced set	Delta
1 2 3	48.67	1 3 8	2.85	1 5 7	48.67	1 7 10	48.67
1 2 4	1.78	1 3 9	48.67	1 5 8	2.85	1 7 11	48.67
1 2 5	48.67	1 3 10	48.67	1 5 9	48.67	1 7 12	0.17
1 2 6	2.85	1 3 11	48.67	1 5 10	48.67	1 8 9	2.85
1 2 7	48.67	1 3 12	2.03	1 5 11	48.67	1 8 10	2.85
1 2 8	2.85	1 4 5	1.78	1 5 12	0.17	1 8 11	2.85
1 2 9	48.67	1 4 6	36.3	1 6 7	2.85	1 8 12	55.29
1 2 10	48.67	1 4 7	1.78	1 6 8	55.29	1 9 10	48.67
1 2 11	48.67	1 4 8	36.3	1 6 9	2.85	1 9 11	48.67
1 2 12	0.17	1 4 9	1.78	1 6 10	2.85	1 9 12	0.1
1 3 4	2.03	1 4 10	1.78	1 6 11	2.85	1 10 11	48.67
1 3 5	48.67	1 4 11	1.78	1 6 12	55.29	1 10 12	0.1
1 3 6	2.85	1 4 12	36.3	1 7 8	2.85	1 11 12	0.17
1 3 7	48.67	1 5 6	2.85	1 7 9	48.67		

Table 3: **Objectives**

Number of objective	Objective
1	Specific total cost (STC)
2	Eco-99
3	Acidification and eutrophication
4	Toxic emissions
5	Land occupation and conversion
6	Carcinogenic effects
7	Climatic change
8	Ionizing radiation
9	Ozone layer depletion
10	Respiratory effects
11	Extraction of fossil fuels
12	Extraction of minerals

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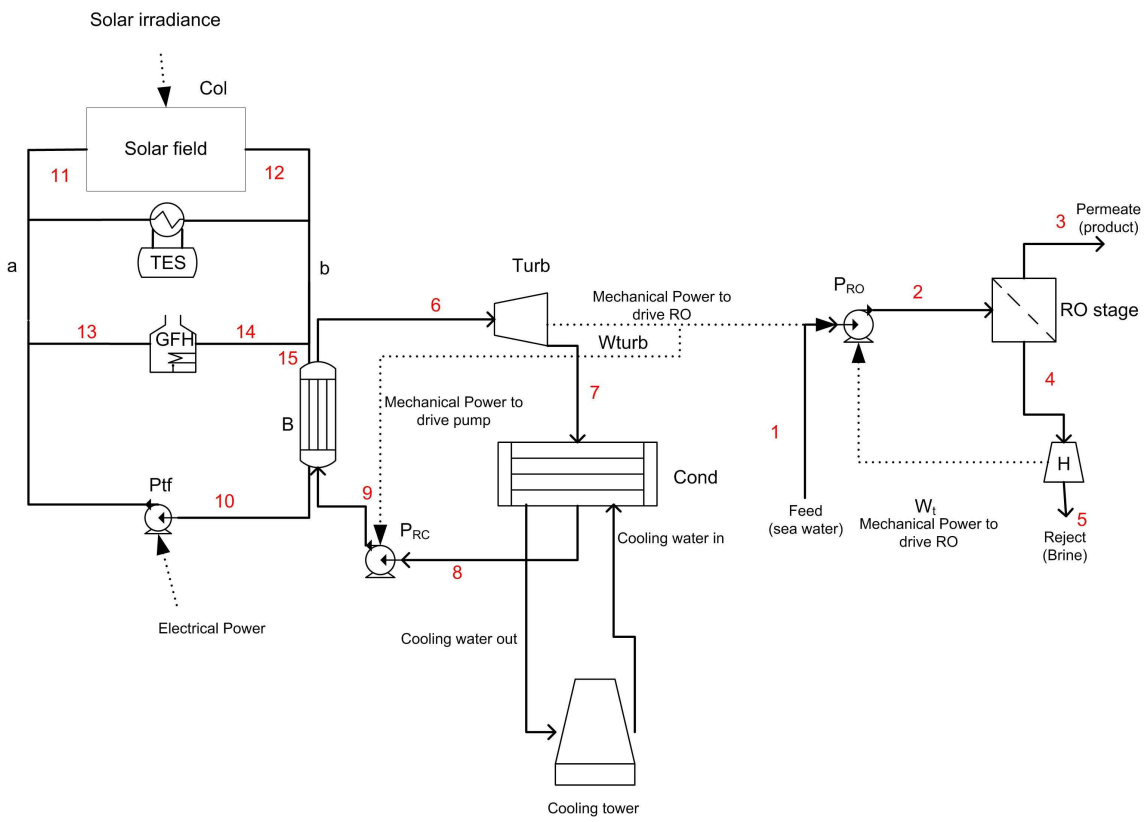
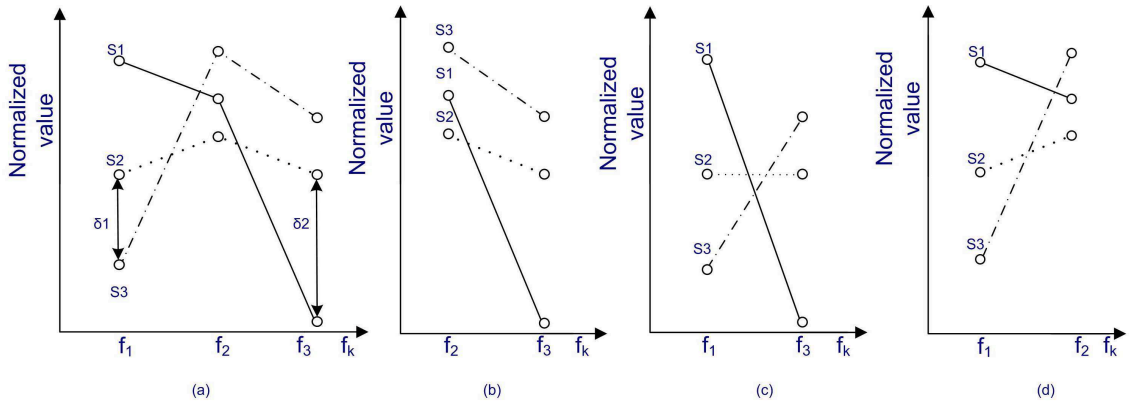


Figure 1: **Scheme of the process**

Figure 2: **Dominance structure of the original(a) and reduced sets (b-d)**



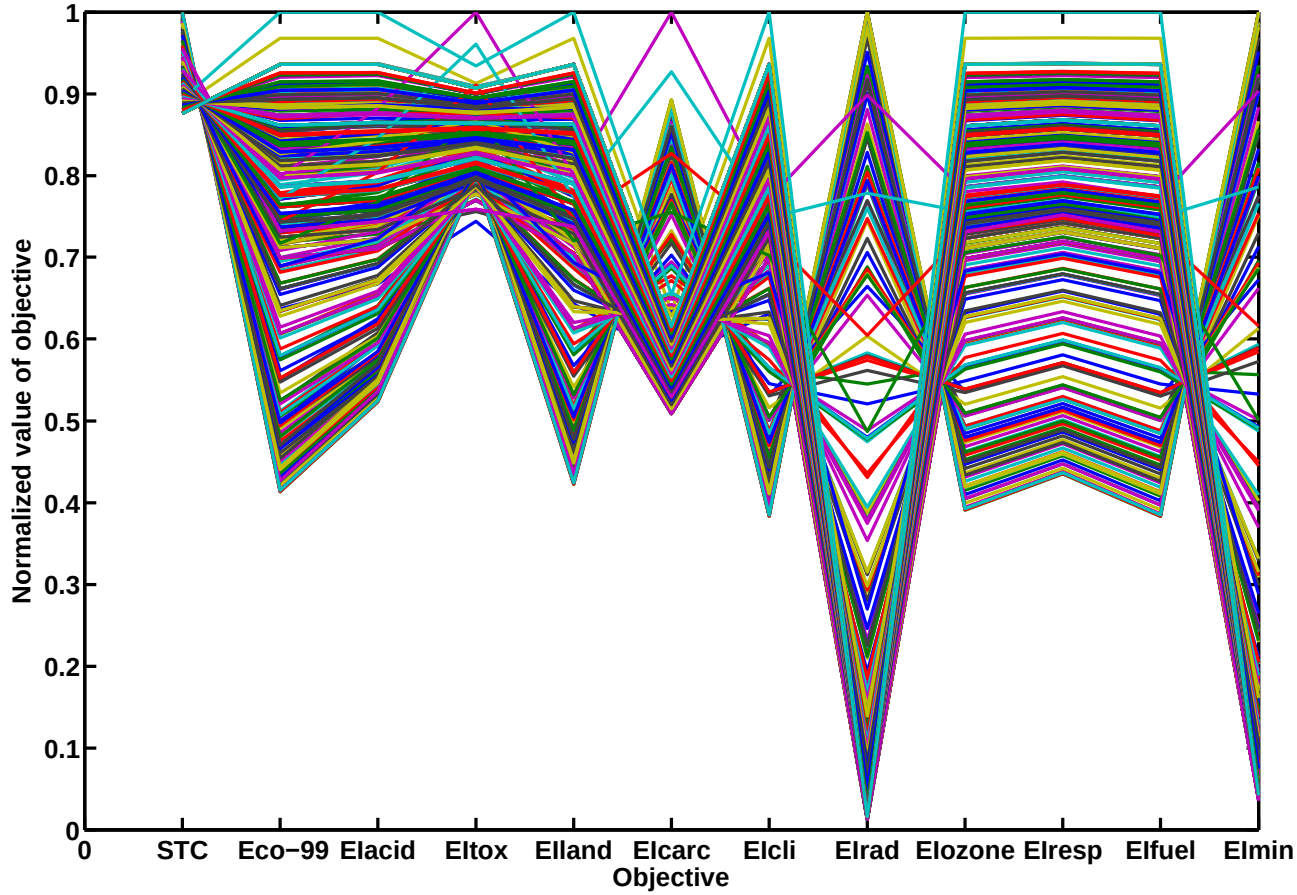


Figure 3: Parallel coordinates plot of generated solutions

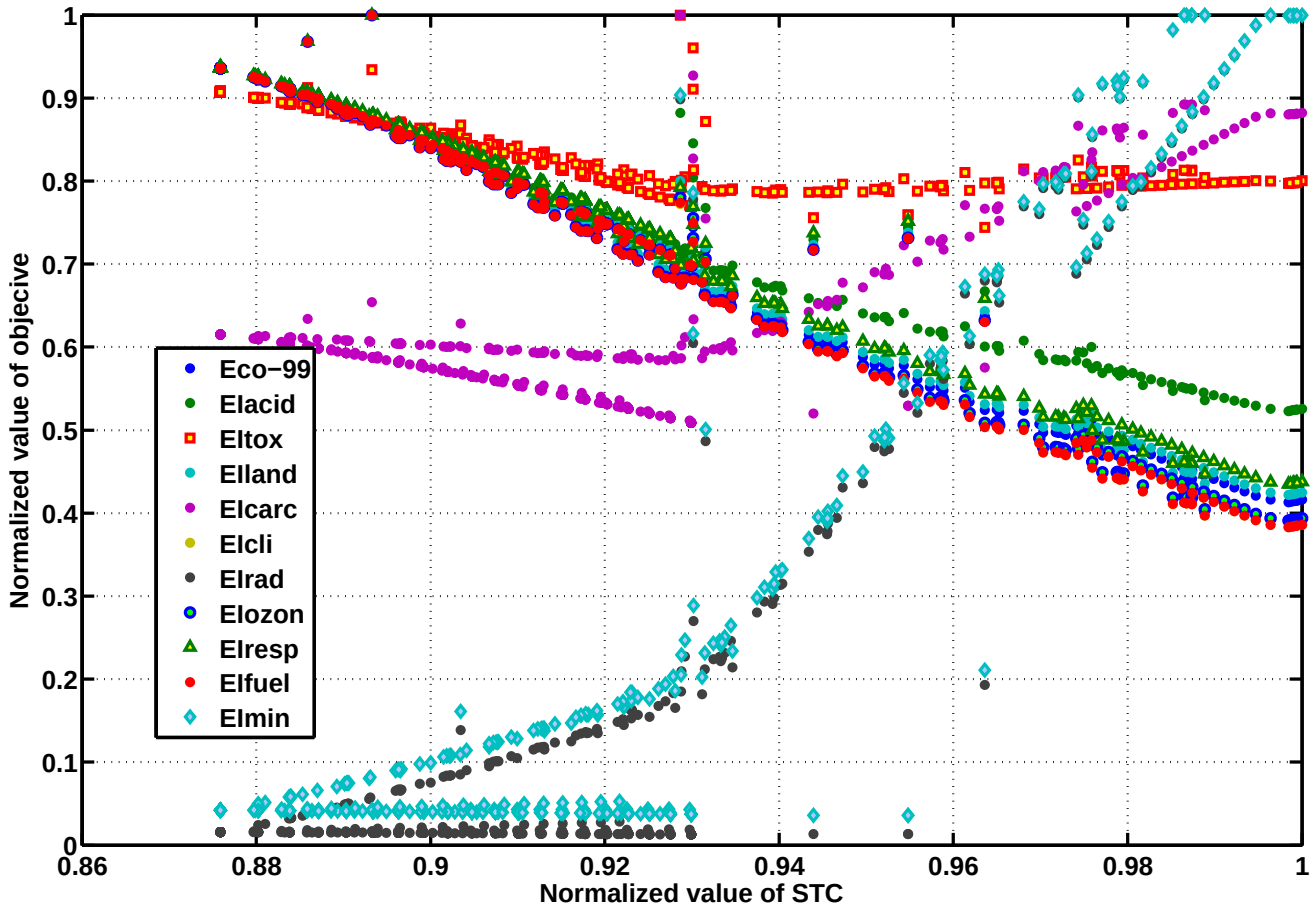


Figure 4: Projections of all the Pareto points resulting from the bi-criteria problems in the 2-D subspaces

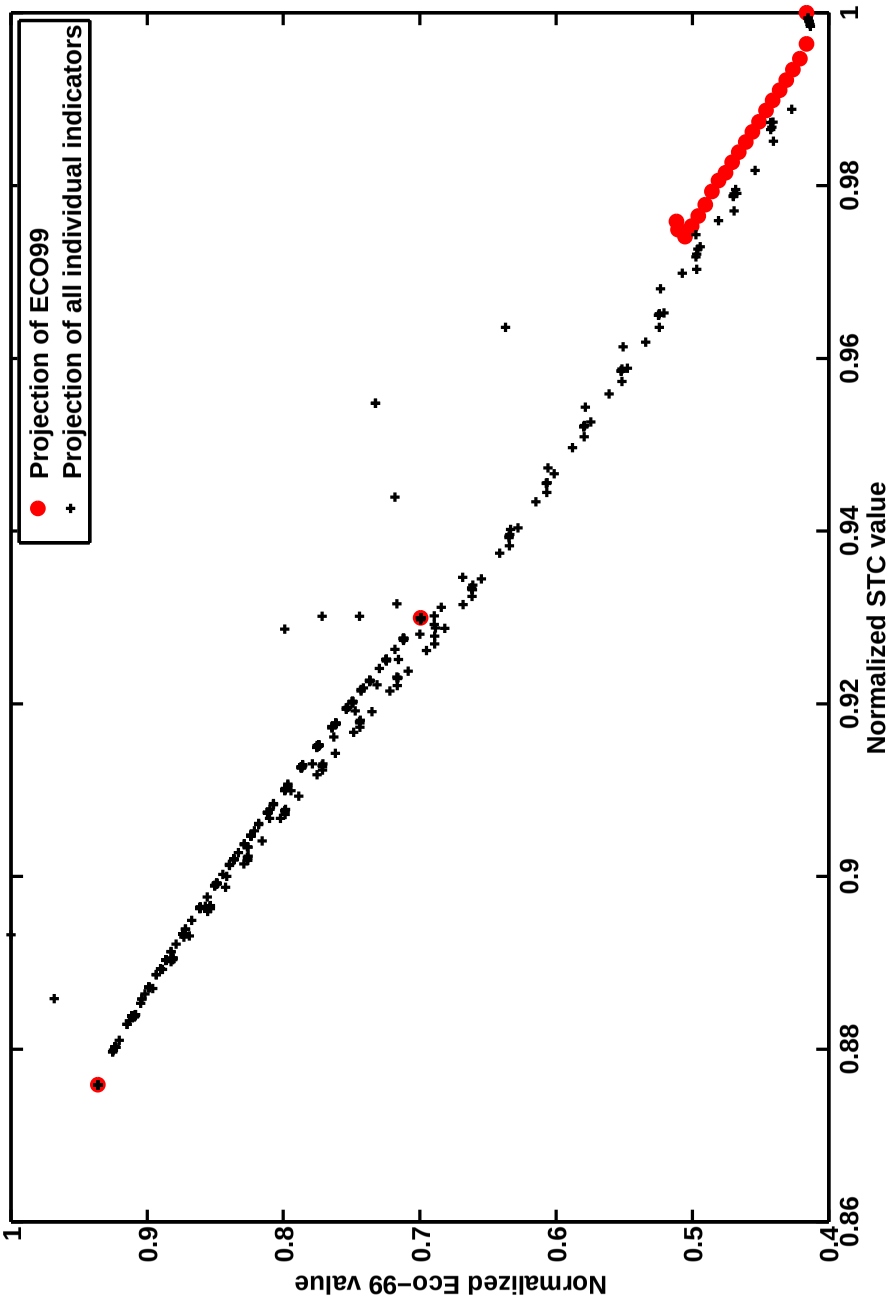


Figure 5: **Projections of the solutions obtained from the bi-criteria optimizations of the Eco-99 vs STC onto the (total Eco-99, STC) space**

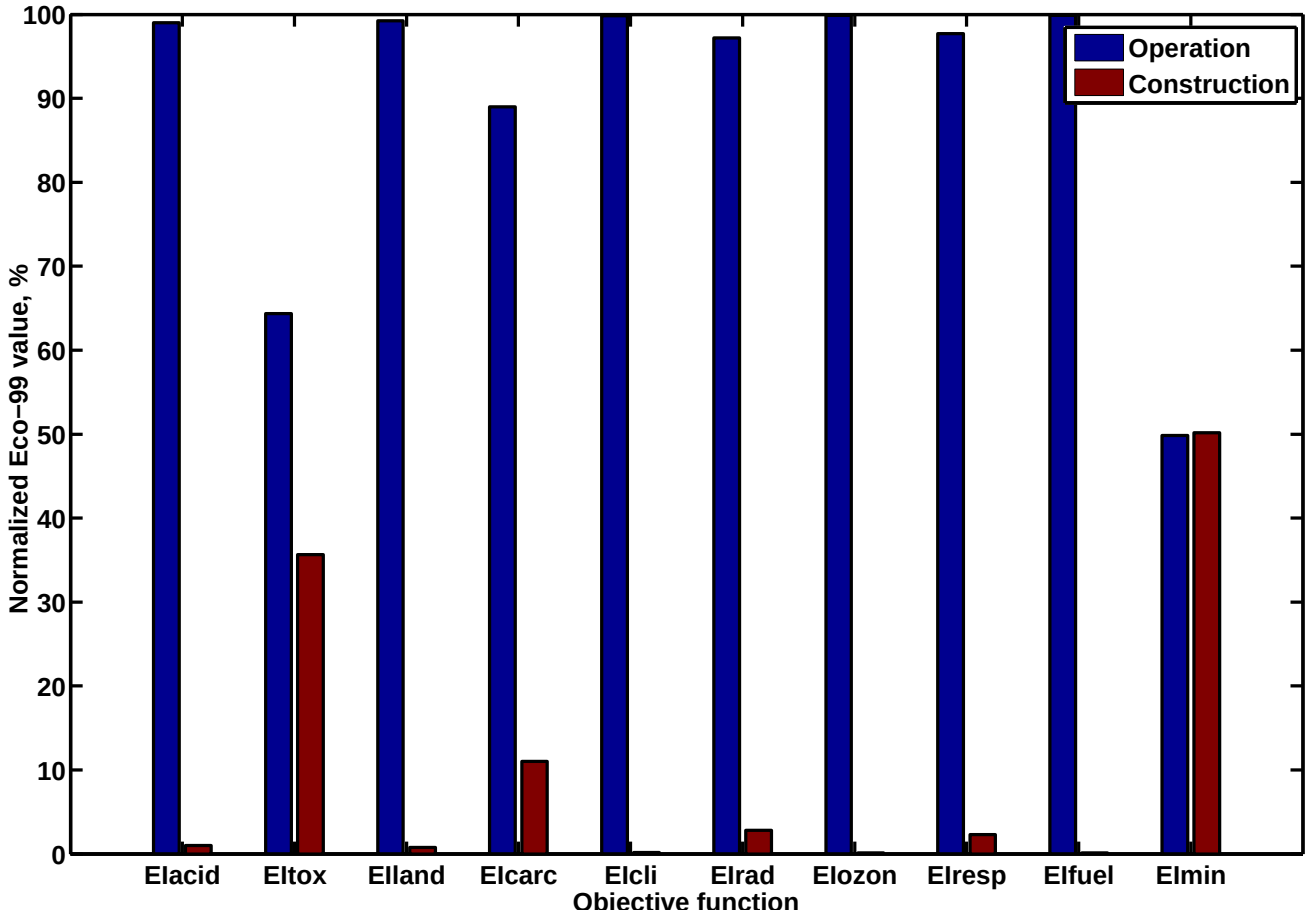


Figure 6: **Environmental impact breakdown for minimum cost solution**

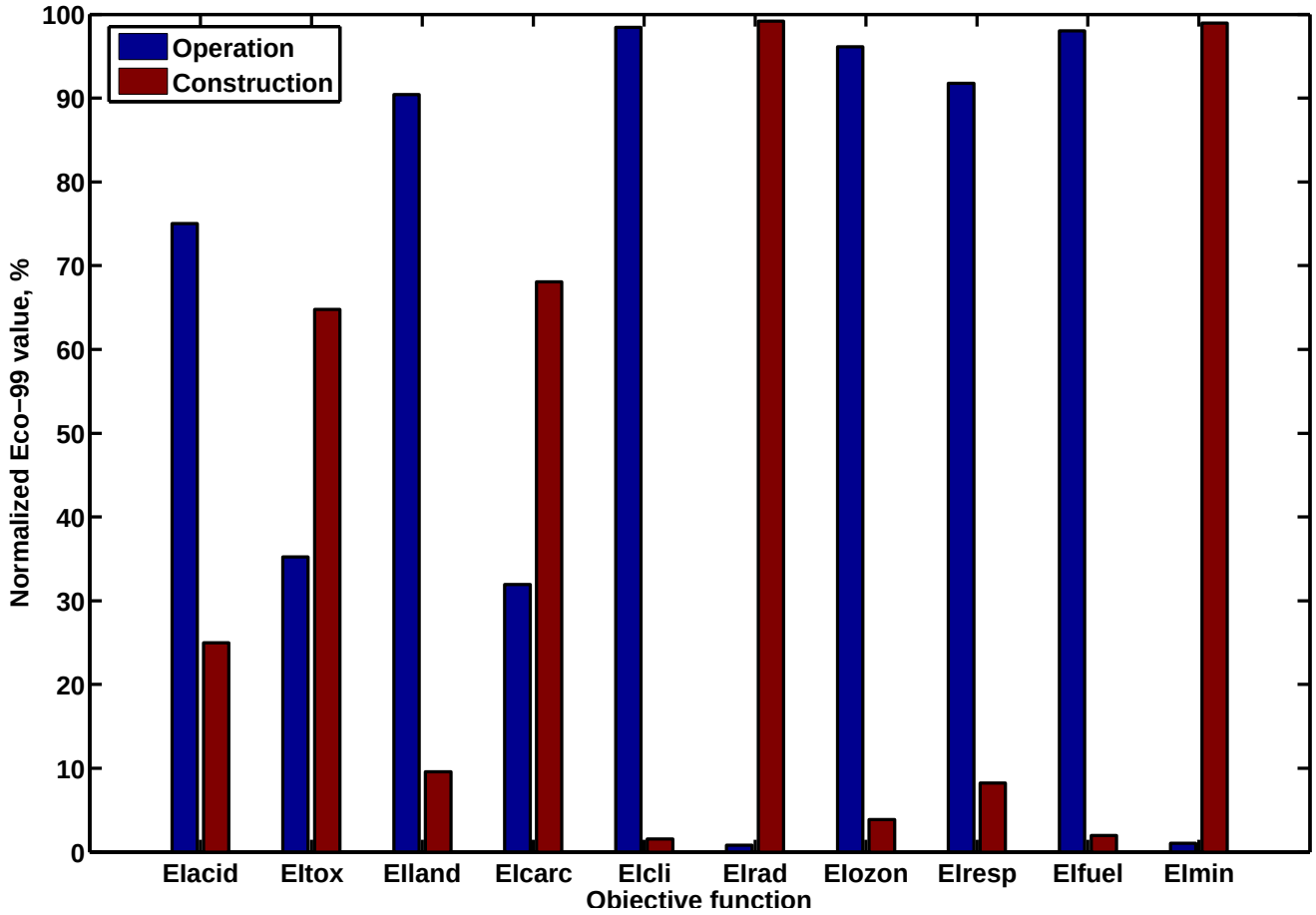


Figure 7: **Environmental impact breakdown for minimum SEI solution**

Appendix. Objective functions

7.0.1. Economic evaluation: Specific total cost

The economic performance of the process is quantified through the unitary production cost per m^3 of water generated (continuous variable STC), which is defined as follows:

$$STC = \frac{Z}{M_d} \tag{2}$$

where Z is the total cost of the plant, and M_d is the total amount of water produced over the whole plant time span LT (in years). The latter term is calculated as follows:

$$M_d = \frac{3600 \cdot m(3) \cdot b \cdot LT \cdot H}{\rho(3)} \tag{3}$$

where H is number of working hours per year.

The total cost of the plant includes the investment and operation cost associated with the solar Rankine cycle SRC (RC with the solar thermal unit and TES) and the RO unit (Z_{SRC} and Z_{RO}, respectively):

$$Z = Z_{SRC} + Z_{RO} \tag{4}$$

The total cost of the SRC accounts for the capital investment cost of every unit of the system ($ICC(k)$) as well as the annual operating and maintenance cost ($COM(k)$). The total cost of the integrated facility accounts also for the cost of natural gas (C_{NG}) and electricity (C_{EL}) during the life time of the plant [34].

$$Z_{SRC} = \sum_k AM \cdot (ICC(k) + COM(k)) \cdot LT + C_{NG} + C_{EL} + C_{TES} \tag{5}$$

$$k = col, turb, cond, B, P_{tf}, P_{RC}$$

where AM is the amortization factor evaluated as follows:

$$AM = \frac{int(1+int)^{LT}}{(1+int)^{LT}-1} \tag{6}$$

in this equation int represents the annual interest rate and LT is plant life span. The operating cost of the RO unit is determined as follows:

$$Z_{RO} = [1.4(CC_{swip} + CC_{P_{RO}} + CC_{mem} + CC_{mod})AM + COM_{RO}] \tag{7}$$

The coefficient 1.4 accounts for the indirect capital cost as well as the cost of the site. CC_{swip}, $CC_{P_{RO}}$, CC_{mem}, CC_{mod} are direct capital costs of seawater intake and pretreatment, RO pump, membrane elements and membrane modules. Details on the calculation of each term in equations 5 and 7 can be found in Appendix 1 of the supplementary material and in [34] .

7.0.2. Environmental impact objective function

The environmental metric to be optimized is the specific environmental impact (SEI), which quantifies the amount of GHG emissions per unit of water produced.

$$SEI = \frac{TGWP}{M_d} \tag{8}$$

where $TGWP$ denotes the total global warming emissions expressed in equivalent tons of CO_2. The value of this variable is determined from the GHG emissions and associated damage factors df(c). These damage factors quantify the GWP impact of the GHG

emissions (measured in equivalent tons of CO_2), expressing them on a common basis.

$$TGWP = \sum_c TLCI(c) \cdot df(c) \tag{9}$$

The total amount of chemical c released to the environment is determined from the LCIs associated with the generation of natural gas and electricity and that associated with the construction phase:

$$TLCI(c) = LCI_{NG}(c) + LCI_{EL}(c) + LCI_{const}(c) \tag{10}$$

The life cycle inventory of emissions associated with the generation of natural gas and electricity are determined as follows:

$$LCI_{NG}(c) = \sum_t \frac{\omega_{NG}(c) Q(k,t) LT \cdot H}{\eta(k)} \qquad k = GFH, \forall c \tag{11}$$

$$LCI_{EL}(c) = \sum_t \frac{\omega_{EL}(c) W(k,t) LT \cdot H}{\eta(k)} \qquad k = P_{tf}, \forall c \tag{12}$$

Here, ω_{NG} and ω_{EL} denote the life cycle GWP emissions associated with the consumption of 1 kWh of electricity and 1 MJ of natural gas burned, respectively. These data are available in environmental databases (Ecoinvent). The LCI of the construction denoted by $LCI_{const}(c)$ is calculated using the following equation:

$$LCI_{const}(c) = \sum_k (LCI(k,c)) + LCI(TES) + LCI_{mem} + LCI_{mod} \tag{13}$$

where the LCIs of equipment unit are determined as follows:

-Pumps and turbine:

$$LCI(k,c) = M(k) \cdot \omega_{Steel}(c) \qquad k = P_{tf}, P_{RC}, P_{RO}, turb, \forall c \tag{14}$$

where $M(k)$ is weight of equipment k, ω_{Steel} is the LCI associated with the production of 1 kg of stainless steel;

- Collector [45]:

$$LCI(k,c) = (Fg \cdot \omega_{FlatG}(c) + Rs \cdot \omega_{Reinf}(c)) \cdot A_{col}; \qquad k = col, \forall c \tag{15}$$

where Fg is the amount of flat glass used in parabolic trough collector per square metre of collector area (kg/m^2); Rs is the amount of reinforced steel used in the parabolic trough collector (kg/m^2) ; $\omega_{FlatG}(c)$ denotes the life cycle emissions per 1 kg of flat glass and $\omega_{Reinf}(c)$ represents the life cycle emissions per 1 kg of reinforced steel;

- Membranes :

$$LCI_{mem}(c) = n \cdot b \cdot A \cdot thick \cdot \rho_{amid} \cdot \omega_{Amid}(c) \qquad \forall c \tag{16}$$

where n is number of membranes per each RO train, b is number of trains, *thick* is the membrane's thickness; ρ_{Amid} is the density of the polyamide and $\omega_{Amid}(c)$ represents the LCI emissions associated with the production of 1 kg of polyamide;

- Modules :

$$LCI_{mod}(c) = b \cdot mod \cdot Mmod \cdot \omega_{FGmod}(c) \qquad \forall c \tag{17}$$

where *mod* is number of pressure vessels per each train ,*Mmod* is the weight of the pressure vessel and $\omega_{FGmod}(c)$ is the impact of 1 kg of fibre reinforced plastic ;

- Boiler, condenser and gas fired heater:

$$LCI(k,c) = A(k) \cdot s \cdot \rho_{steel} \cdot \omega_{Steel}(c) \qquad k = B, cond, GFH, \forall c \tag{18}$$

where $A(k)$ is heat transfer area, s is the thickness of the tubes in the heat exchangers and ρ_{steel} is the density of steel;

- Storage [46, 47]:

$$LCI_{TES}(c) = (\omega_{Molt}(c) \cdot Refmolt + \omega_{Reinf}(c) \cdot Reinf + \omega_{Reinf}(c) \cdot Refsteel + \omega_{Foam}(c) \cdot Reffoam + \frac{\omega_{Conc}(c) \cdot Refconc}{\rho_{conc}} + \omega_{Brick}(c) \cdot Refbrick) \cdot MS/MSref \quad \forall c \tag{19}$$

where $\omega_{Molt}(c)$ represents the life cycle emissions associated with the production of 1 kg of molten salts(KNO_3); $Refmolt$ is the referential amount of molten salts in the storage; $Refreinf$ denotes the referential amount of carbon steel ; $\omega_{Reinf}(c)$ represents the LCI emissions associated with the production of 1 kg of reinforced steel; $Refsteel$ denotes the referential amount of reinforced steel; $\omega_{Foam}(c)$ represents the LCI emissions associated with the production of 1 kg of foam glass; $Reffoam(c)$ is the referential amount of foam glass; $\omega_{Conc}(c)$ denotes the LCI emissions associated with the production of 1 m_3 of concrete; $Refconc$ is the referential amount of concrete; rho_{conc} is the density of concrete; $\omega_{Brick}(c)$ represents the LCI emissions associated with the production of 1 kg of refractory brick; $Refbrick$ is the referential amount of refractory brick; MS denotes the weight of the thermal mass and $MSref$ is the referential value of the thermal mass. The thermal mass consists of molten salts and silica sand. The weight of the thermal mass (MS) associated with the maximum thermal energy (CAP), is calculated as follows:

$$MS = CAP \cdot MSref/(\Delta T_{stor} \cdot (C_{ms} \cdot Refmolt + C_{sil} \cdot Refsil)); \tag{20}$$

where C_{ms} and C_{sil} are the specific heat of molten salts and silica sand respectively and ΔT_{stor} is the temperature difference between the top and bottom of the storage tank.